Risk and reward – is it all in our heads? A short survey of neuroeconomics

Alas, Renato M; Kumar, Kuldeep; Nabin, Munirul H.; Bhattacharya, Sukanto

Published in:
Proceedings of the 41st Australian Conference of Economists

Risk and reward – is it all in our heads? A short survey of neuroeconomics

R. M. Alas*, K. Kumar*, M. Nabin** and S. Bhattacharya**[1]

*School of Business, Bond University, Gold Coast, QLD 4229, Australia

**Deakin Graduate School of Business, Deakin University, Burwood, VIC 3125, Australia

Abstract

This is a mini review on the recent developments in the intriguing field of neuroeconomics that falls within the overlap between a number of contributing disciplines in the social and natural science – economics, psychology, neuroscience and medical imaging being the major ones. We start by providing a brief background of neoclassical approaches to studying decision-making and work our way through the development of the field with increasing inputs from the behavioral sciences till the current point when the *extra-economic* inputs to the study of economic decision-making are no longer coming only from the cognitive psychologists but also from the computational neuroscientists and neuro-physiologists. We explore the methodological challenges and opportunities of this new, inter-disciplinary field of intellectual enquiry; and conclude by considering some of the major roadblocks that the field is faced with and finally positing some interesting future research directions.

Key words: neuroeconomics, behavioral economics, decision-making, rational choice, brain imaging

1 Introduction

Utility theory and the rational choice model have dominated economic decision-making for the better part of last two hundred years. Before delving into the nature of neuroeconomics, it is desirable to briefly discuss the

[1] Corresponding author: e-mail sukanto@deakin.edu.au, facsimile +61392445533

conventional approaches to the study of economic decision-making that it purports to replace (or at least heavily complement). The rational choice model (hereafter RCM) has dominated formal theorizing of economic decisions over a substantial length of time and have even staged a comeback of sorts in recent times (Green and Shapiro, 1996). The basic RCM rests on some fundamental premises – individuals have a number of alternative courses of action which may be ranked in their order of preference and there is an inherent logic in such preference ordering such that if an alternative is preferred over another one then a third alternative that is preferred over the former will also be preferred over the latter. Following such an *objective*, *complete* and *transitive* ranking of the available alternative courses of action according to his/her *revealed preferences*; the individual would select the one that gets the highest rank (Kreps, 1990). Preferences are formally represented via a "utility function" which again; has to have certain fundamental characteristics. If an action has a positive result then, intuitively, an individual is expected to repeat that action as he/she would want to enjoy more and more of the "positives" and by doing so his/her level of utility would therefore rise. So utility functions need to have a positive slope i.e. a curve sketched by such a function would have to be rising to the right of the origin. However too much of anything can be bad – so repeating one action again and again i.e. choosing one alternative repeatedly over others would be expected to reduce the subsequent "positives" such that beyond a certain point the curve sketched by an utility function would be expected to stop rising and eventually head downwards (as the "positives" turn into "negatives" due to an overdose). So utility curves must be rising to the right of origin (i.e. have positive slopes) but at the same time they must be rising in diminishing marginal increments. Any preference ranking that has the properties of completeness and transitivity may be formally represented via a utility function so long as the number of alternative choices is finite (Mas-Collel, Whinston and Green, 1995). In the presence of explicit restrictions under which certain courses of action may be taken by the individual, any economic decision problem adopting the RCM devolves to a mathematical problem of *constrained optimization*.

In its most basic form, RCM assumes that the results from the actions are certainly known. In an extended RCM, 'uncertainty' is introduced in the outcomes and we enter the realms of 'expected values'. Under such an extended version, a probability value is assigned to the result from each of the available alternative courses of action. As the individual is bound to take one of the courses of action (since taking no action is also one of the alternatives), the set of alternative courses of action is a mutually exhaustive set such that the separate probabilities sum to unity thus constituting a valid probability distribution. Then the *expected utility function* is obtained as a sum of the product of each result (measured in some units of value) with its associated probability; summed over all the available courses of action for which the results can be objectively measured. It is here that matters can get particularly intriguing. To illustrate let us consider a 'game' where an individual player would have to perform a daredevil act e.g. driving fast along a narrow, mountainous road in the dark without headlights in order to get to a very large monetary reward at the end of the road if the player can make it. If the player is an extremely skilled driver then he/she stands a reasonably good chance of pulling it off and getting the prize. But even the world's best driver would run a finite risk of failing to make it and having a serious or even fatal accident. In such an event the expected utility function will break down as one of the probable results is an *infinite loss* (i.e. death) no matter how small the associated probability. Even then; there would be a few people who would be willing to take up such a challenge (Nofsinger, 2002). If they decided to take up the challenge, such players would thereby be acting irrationally in contravention of the predictions of expected utility theory. Although it is a rather extreme decision scenario, this anecdotal example helps to illustrate the lacuna of an expected utility paradigm.

It is only in the last three decades or so that the role of "irrationality" in human decision-making has been receiving a fair deal of attention mainly owing to the ground-breaking work of Kahneman and Tversky (1979) where they postulated their *prospect theory* as a formal departure from the expected utility theory paradigm of RCM. A few years following that Hershey, Kunreuther and Schoemaker (1982) observed that a choice between the same pair of certain and risky results was largely determined by whether the decision was represented as a "gamble" when the individuals displayed risk-seeking behaviour, or as an "insurance" when they suddenly became risk averse. The next two decades were clearly dominated by the behaviorists and *behavioral economics* gained a strong foothold within the academic ramparts as a sub-field of both economic as well as the behavioral sciences. Although Schultz (2008) has criticized prospect theory by claiming that it lacks a coherent framework, Kahneman and Tversky's work has to be credited with having opened Pandora's Box by firmly establishing behavioral economics as a recognized discipline. Loewenstein et al. (2008) have in fact argued that human beings are inherently "fallible creatures" and not the perfect maximizers of utility as assumed by the neoclassical utility theory; and as such any study of economic decision-making as a subset of overall human behavior should therefore borrow extensively from the discipline of psychology which recognizes and explores human fallibility.

Human behavior is extremely difficult to measure and over the ages economists have been preoccupied with developing mathematical techniques to devise fantastic theories and make lofty predictions without ever bothering to measure thoughts or feelings directly. The birth of behavioural economics made it quite plausible for economists to actually gain a better handle on crucial but highly subjective issues like satisfaction, happiness and guilt by taking recourse to psychometric methods. But at the end of the day even those psychological measures have now started to be brought into question as they typically depend on the veracity of the designed questionnaires, the accuracy of participants' responses etc. Indeed one of the big criticisms of behavioral economics is that it cannot empirically ratify some of its own theories owing to the fact that measurements are either impossible or at best only anecdotal observations can be made (Camerer, Loewenstein and Prelec, 2004). It is against this backdrop that "neuroeconomics" as a discipline made an appearance and is making rapid progress by exploring methods of making robust measurements of the latent drivers behind human decisions.

What is neuroeconomics?

Neuroeconomics is born out of a confluence of physiological, behavioral and social sciences devoted to the study of human decision-making involving pleasure (i.e. rewards) and pain (i.e. risks) (Zak, 2004; Clithero et al., 2008). That economists could learn something from biologists is however not a very new idea – Simon (1979) opined that evolutionary theories could offer explanations to complex socio-economic phenomena that seemed random. Simon's vision essentially gave birth to the field of *bioeconomics* – a field that was subsequently enriched and expanded through the works of Hirshleifer (1985), Landa and Gheslin (1999) and Reason (2000). Zak (2004) opined that neuroeconomics is a natural extension of bioeconomics into the domain of behavioral economics – while bioeconomics focuses on the bio-dynamics of behaviour, behavioural economics focuses on the role of psychology in decision processes and neuroeconomics focuses on the mechanisms underlying choice of an action. In terms of its scope then neuroeconomics would be concerned with all neuro-physiological structures, psychological constructs as well as intuitive economic logic that determine choice from a finite set of alternative courses of action with different results under a range of physical/mental/emotional/environmental conditions. Camerer (2007) has stated that the discipline of neuroeconomics can even act as an important source of insights on neuroscience experimental designs as the complex cognitive processes to be studied within neuroeconomics can be effectively grouped under the crisp sub-categories of neuro-anatomic and neuro-physiological events.

Camerer, Loewenstein and Prelec (2004) have contended that most human decision-making has two components – one is automatic (i.e. occurs spontaneously) while the other is judgmental (i.e. non-spontaneous and may involve a conscious, deliberative process). Such behavior is produced mainly by the coordinated activates of four lobes of the brain and these are: (i) *frontal*, (ii) *parietal*, (iii) *occipital* and (iv) *temporal*. The *frontal* lobes play crucial role in making plan, cognitive control and in establishing coordination among other lobes of the brain to produce a particular behavior. The other lobes, *parietal*, *occipital* and *temporal*, govern motor action, visual processing and emotion/recognition/memory respectively. In other words, these four lobes process/assimilate the information to make any kind of decision. Further, as argued by Camerer, Loewenstein and Prelec (2004), the brain, when making a rapid decision, tends to ``overwrite" past knowledge. Indeed, such "overwriting" is quite possibly a very key factor making us part ways with the mathematical predictions of RCM.

It has been observed that certain behaviours that are clearly established to occur automatically are subsequently misinterpreted by human experimental subjects as having occurred via a process of conscious deliberation (Wolford, Miller and Gazzaniga, 2000). It is therefore apparent that although a decision could arise purely out of a series of neural activities that are entirely inaccessible to the cognitive process, one can erroneously attribute the same to a conscious act of cognitive deliberation. It has been already been firmly established that economic rewards are linked to primal drives that governs the neural pathway of pleasure and pain (Tobler, Fiorillo and Schultz, 2005). This neural pathway is known as the *dopamine channel* and dopamine neurons (nerve cells) have been observed to be sensitive to the size of the reward (Drevets et al., 2001); and evidence has also been found for a positive correlation between the firing of the dopamine neurons and the experimental subjects reporting to be spontaneously feeling "upbeat" (Volkow et al., 2002). This is significant as a specific decision could be pre-ordained given a certain level of reward.

For purpose of illustration let us consider a decision situation modelled as a "coordination game". A coordination game is game theoretic decision model that reveals the effects of having foreknowledge of an opponent's behaviour. The most crucial feature of this kind of game is that it involves multiple equilibriums, which may or may not be ranked; and the *selection of equilibrium* is a big issue in this sort of game, in particular, when the game does have ranked equilibriums. Several ways have been proposed to explain the selection of equilibrium among which, two are particularly prominent. The first one proposed by Harsanyi and Selten (1988) focused on information processing which may provide a signal to his rival player in selecting the equilibrium strategy; while the second one proposed by Kandori, Mailath and Rob (1993) is based on "natural selection" borrowed from evolutionary dynamics where focus is made on each agent's learning behavior. It may also possible to explain such selection of equilibrium with the help of neuroeconomics. We strongly suspect that a neuroeconomics approach could provide a strong support to the proposition of Kandori, Mailath and Rob (1993), where they allow for a given probability of making mistake in the individual's learning pattern. Indeed, neuroeconomics can go one step further by helping to explain the basis of making such mistake. For example, one can argue that it is the brain's overwriting previous information that leads us to make a mistake. The following provides an example:

Let us imagine that two persons have separately set out for a walk through the forest when they suddenly come face to face with a bear at the same time. They can either choose to run; or stand their ground and try to scare off the bear. If both of them stand their ground they can very likely scare off the bear and that way they will both escape unhurt. Let 1 represent the outcome of escaping unhurt. However if only one of them decides to run for it (and escapes unhurt), the one who stays back will be badly mauled. Let 0 represent the outcome of getting badly mauled. If they both decide to run for it the bear will charge and the slower of the two will get badly mauled while the faster will escape unhurt. Therefore, each person faces two outcomes with equal probability – escaping unhurt (probability ½) or getting mauled badly (again; probability ½). Therefore, his expected payoff from such strategy will be {(½) x (1)} + {(½) x (0)} = ½. The resultant payoff matrix is depicted in Figure 1 below.

INSERT FIGURE 1 ABOUT HERE

The above game has two equilibriums (½, ½) and (1, 1) and clearly these equilibriums are *Pareto-ranked*, where (1, 1) is *Pareto-dominant.* It would appear from the above payoff matrix (which has been depicted from the viewpoint of Person 1) that in the absence of foreknowledge about Person 2's chosen action he would decide to run for it as that would maximize his own chance of escaping unhurt. Indeed, the strategy 'run for it' is each agent's weakly dominant strategy. If they apply a rational, deliberative process they ought to stick together and stand their ground to maximize the chances of both escaping unhurt. But when in such a helpless and obviously highly stressful situation, human decisions are rarely deliberative and are rather "spur of the moment" acts with no cognitive components at all. It could of course be that the "spur of the moment" decision comes out the same as the one that would have been taken if a cognitive process was employed. However it could quite easily be a different one as well. The point is, spontaneous decisions are processed within our brains and we have little or no control over what we decide in such circumstances as the brain is on auto-pilot. In such circumstances it would be of course helpful to know what underlying latent mechanisms are involved that would actually govern the decision-making rather than a deliberative process over which the decision maker has control. This is precisely where neuroeconomics purports to be able to make a big contribution to the decision sciences. Indeed, though the choosing the strategy `run for it' is weakly dominant, given the threatening circumstances of facing a wild bear, neuroeconomics suspects that the *Pareto-dominant* equilibrium (1, 1) is not very likely to be attained.

Methodology of neuroeconomics: challenges and opportunities

It would appear that a heavily cross-disciplinary subject like neuroeconomics would have a plethora of adoptable methodologies that it can choose from and call its own. However things are not that simple. The main hurdle stems from the fact that the three major contributing disciplines – economics, psychology and physiology rarely see eye-to-eye with each other! Economists have always preferred to keep matters involving human emotions and feelings out of the purview of their somber mathematical models. That didn't actually endear them to behavioral scientists seemingly derisive of anything that seems to be able to exist independent of human frailties. And the hitherto unresolved "mind versus matter" debate hasn't really helped the cause with physiologists and psychologists continually in conflict over whether our brains are in charge of our minds (as the neurophysiologists would have us believe) or whether it is our minds that are ultimately in charge of nearly everything (as the cognitive psychologists would like to view things). The result is that although proponents from all the three major contributing disciplines agree that they must all come together to address the problem of human decision-making, they are at the same time actively debunking each other's methodological approaches!

However some common grounds have been cemented and there is hope of further consolidations in the future. The burgeoning growth of "experimental economics" is arguably the most promising development in recent times that reflect an obvious influence of the bio-behavioral sciences on the accepted methods of economic enquiry. While it is still an open question as to whether social sciences (and economics is *still* a social science) can ever be as amenable to laboratory-based experimental studies as natural sciences, there are some obvious merits of being actually able to "keep everything else unchanged". However the biggest issue is whether staged social experiments conducted within the confines of a contrived setting are truly reflective of the real goings-on? Nevertheless economists have picked up a lot of experimental methods in recent times from behavioral sciences. And this augurs well for the future of neuroeconomics as it will of course entail a lot more laboratory experimentation than any other field of economics as it tries to look inside the ultimate black box – human brain.

Any consistent and reliable data that directly relates to the underlying processes as they are brought to light contributes both to better theorization and at the same time to better means of falsifying theories; and this is one of the reasons behind rapidly growing acceptance of neuroeconomic studies (Cacioppo and Nusbaum, 2003). Brain imaging studies using real-time *functional magnetic resonance imaging* (fMRI) is a well-accepted methodological approach that is quite specific to neuroeconomics (Sanfey et al., 2003; Khoshnevisan et al., 2008). Image construction in fMRI depends on varying rates of relaxation among the biological tissues due to their intrinsic nature. Put simply, after the removal of an applied magnetic field the alignment of hydrogen in the water molecules present in the various biological tissues returns exponentially to its original state during the relaxation process with varying rates – T_1, T_2 and T_2^* (Logothetis, 2008). T_1-weighted images use a gradient echo sequence with short echo and repetition times, resulting in a contrast between grey and white matter. T_2 uses a long echo time and repetition time, where water appears brighter and biological tissue appears darker. Therefore, the differences in the relaxation rates necessarily reveal the anatomy of the brain, and because of the dynamic nature of the brain tissue, these variations can be interpreted as time changes during the composition of the images, also called T_2^*- weighted imaging, which is really the base process in generating fMRI images.

By applying brain imaging techniques to study economic decision-making, researchers are able to break down the inherent processes and mechanisms underlying the choice of a specific action from within a set of alternatives in terms of both its structural (i.e. biological) as well as cognitive (i.e. behavioural) components. The usual pattern of such experiments involves taking brain images in real time of the experimental subjects while they are engaged in some specific decision-making task. The fMRI images reveal the exact sections of the brain that are most active while performing the given tasks and some of the findings can indeed be quite surprising.

For example, Sanfey et al. (2003) did an fMRI imaging study of experimental subjects who received either fair or unfair monetary offers in an *ultimatum* game. They found that when players received unfair offers there was a high activity observed in the *insular cortex* (a section of the brain which generates feelings of revulsion) as well as in the *anterior cingulate cortex* (a section of the brain that is heavily involved in cognitive processing). The distinctive patterns on the fMRI images were indicative of the subjects trying to reconcile between their feelings of revulsion at having been given an unfair offer with their want for whatever monetary reward was there to be had. If the *insular cortex* activity was more active than the *anterior cingulate cortex*, the subject would be seen to end up rejecting the unfair offer. Khoshnevisan et al. (2008) conducted fMRI imaging of experimental subjects while they were engaged in three tasks of varying monetary risk levels. They found that risky choices and risk-seeking mistakes were both preceded by activation of a section of the brain called *nucleus accumbens*, while both riskless choices and risk-aversion mistakes were preceded by activation of a different section called the *anterior insula*. These results were consistent with the hypotheses that the *nucleus accumbens* represents gain prediction (Knutson et al., 2001) and the *anterior insula* section represents loss prediction (Paulus et al., 2003).

While experimental studies in neuroeconomics could also make use of other available neuro-physiological measurement techniques e.g. *magnetoencephalography* (MET) and *positron emission tomography* (PET), by far most experimental studies have relied on some form of MRI due to better spatial resolution (Wager et al., 2007). With the continuing development of modern neuro-imaging methods, it is now increasingly becoming possible to accurately relate specific cognitive processes to the latent neural activities that go on inside the brain and thereby understand which decisions (and to what extent) are under the cognitive control of the decision maker. This is definitely an improvement over traditional psychometric methods of measuring behaviour as neuro-physiological measurements essentially carry a higher degree of validity compared to conventional behavioural measurements because the former offer more direct and unmediated measures (Cacioppo and Nusbaum, 2003).

Conclusion: is neuroeconomics for real or is it only in our heads?

Levine (2003) has argued in defence of RCM that predicting economy is <u>not</u> like predicting the weather – and that's the reason why one should expect markets to follow the path that people fear them to follow. If people fear that the market will crash they will start offloading (selling off) their assets. If a large enough number of people believe in that fear then there will be enough selling pressure created to cause the market to crash. It does not mean that the market mechanism per se has failed or that RCM couldn't predict what was coming – it is rather a self-fulfilling prophecy that has nothing to do with the fundamental economic forces and mechanisms. However one could turn Levine's argument on its head and use it to attack the RCM that he has sought to defend. If RCM is something that is pre-destined to fail in the face of reality aren't we better off looking somewhere else?

Levine (2003) also argues against neuroeconomics questioning the need for having such a discipline in the first place as according to him it wouldn't really help to answer questions regarding human behaviour any more than a knowledge of the inside of a CPU would help a computer programmer to write a better software code. However the fact of the matter is the software code will in effect be interacting with the underlying hardware and without any knowledge of, for example, the speed of the processor or the amount of available RAM space etc. one could not effectively write a software code without running into issues at the time of compilation. However, analogies with the computer aside, it is important; as we have discussed in an earlier section, to know whether and to what extent is a decision under the cognitive control of the decision maker and is not automatic. Because if a decision is automatic i.e. it does not internally involve a deliberative process; then how can one shape such a decision so as to maximize some measure of expected utility within (or even without) a given set of constraints? There is obviously a need to identify whether a decision is under the decision maker's control before one can run it through any RCM-type optimization model. If, as is known to be the case with the dopamine channel, a certain level of 'stimulus' would always make an individual feel enough "upbeat" to put all his savings into junk bonds then no amount of mathematical analysis or economic theorizing can influence such a choice!

The pertinent question then is approximately what proportion of our day-to-day economic decisions can be ascribed to the internal "hard wiring" of our neural connections and endocrinal system? Also within those decisions that are seemingly available to our cognitive faculties to be subjected to "soft analysis", which ones are we really deliberating on and which ones just entail spurious deliberations? It seems that a significant amount of future research efforts in the neuroeconomics area will need to be devoted to answer these types of questions. Neuroeconomics has a lot of methodological commonalities with computational neuroscience and there is a lot of scope for mutual enrichment. An interesting methodological approach to computationally simulating the processes of economic decision making in the human brain was developed by O'Reilly and Munakata in 2000 when they developed an Artificial Neural Network (ANN) model of the *basal ganglia* (BG). This computational model was subsequently improved and used in a number of cognitive situation studies (Frank, *Loughry and O'Reilly,* 2001; Norman and O'Reilly, 2003; Frank, Rudy and O'Reilly, 2003; Atallah *et al.,* 2004; Frank, 2005; Frank and Claus, 2006 and Frank and O'Reilly, 2006). The extended model developed by Frank (2005) includes a competing process of the indirect pathway, from the *striatum* to the *external segment globus pallidus* (GPe), to the *internal segment globus pallidus/substantia nigra pars reticulata* (GPi/SNpr); previous models did not take into account these segments. Frank's model also covers substantia nigra pars compact/ventral tegmental area (SNpc/VTA) and allowed a complete simulation of the role of neuro-modulator dopamine (DA) in decision-making.

However the most significant contribution to knowledge from advances in neuroeconomics could come in the unlikely form of cures to diseases like dementia and also successful rehabilitation following traumatic brain injuries. Although not directly related to clinical neurology, exploratory neuroeconomics; especially via experimentations using real-time brain imaging techniques on complex choice behavior; could help to gather information about the functioning of healthy human brain in terms of its capabilities of high-end decision-making. Several neurological conditions are related to a dysfunctional DA, such as Parkinson's disease, attention deficit/hyperactivity disorder (ADHD) and Schizophrenia. By modelling the dysfunctional areas of the brain, researchers can better understand the role these regions play in a healthy brain (Cools *et al.*, 2002; Frank, 2005; Frank and Reilly, 2006). Such information could be used to set up an ANN model where researchers could 'switch off' certain sections (corresponding to damaged areas of the brain) and see the effect on decision quality. It would potentially reveal the sections of the brain where most of our high-end decisions devolve and in case of damage to those sections, could reveal alternative neural pathways that could be assigned some of those tasks.

It is our view that neuroeconomics has a definite role to play in a better and more complete understanding of the human decision making processes in general and economic decision making processes in particular. It is *literally* all in our heads but in a positive sense – and in neuroeconomics we finally have a discipline to bring it all out!

****

References:

Atallah, H. E., Frank M. J., and O'Reilly, R. C., 2004. Hippocampus, cortex, and basal ganglia: Insight from computational models of complementary learning systems. Neurobiology of Learning and Memory 82, 253-267.

Cacioppo J. T. and Nusbaum, H. C., 2003. Component processes underlying choice. Proceedings of the National Academy of Sciences 100, 3016-3017.

Camerer, C. F., 2007. Neuroeconomics: Using Neuroscience to Make Economic Predictions. The Economic Journal 17, C29-C42.

Camerer, C. F., Loewenstein, G. and Prelec, D., (2004). Neuroeconomics: Why Economics Needs Brains. Scandinavian Journal of Economics 106(3), 555-579.

Clithero, J. A., Tankersley, D. and Huettel, S. A., 2008. Foundations of Neuroeconomics: From Philosophy to Practice. PloS Biology 6(11), 2348-53.

Cools, R., Clark, L., Adrian, M. O. and Robbins, T. W., 2002. Defining the Neural Mechanisms of Probabilistic Reversal Learning Using Event-Related Functional Magnetic Resonance Imaging. The Journal of Neuroscience 22 (11), 4563-4567.

Drevets, W. C., Gautier, C., Price, J. C., Kupfer, D. J., Kinahan, P. E., Grace, A. A., et al., 2001. Amphetamine induced dopamine release in human ventral striatum correlates with euphoria. Biological Psychiatry 49, 81-96.

Frank, M. J., 2005. Dynamic Dopamine Modulation in the Basal Ganglia: A Neurocomputational Account of Cognitive Deficits in Medicated and Nonmedicated Parkinsonism. Journal of Cognitive Neuroscience 17(1), 51-72.

Frank, M. J. and Claus, E. D., 2006. Anatomy of a Decision: Striato-Orbitofrontal Interactions in Reinforcement Learning, Decision Making, and Reversal. Psychological Review 113(3), 300-326.

Frank, M. J., Loughry B. and O'Reilly, R. C., 2001. Interactions between frontal cortex and basal ganglia in working memory: A computational model. Cognitive, Affective, & Behavioural Neuroscience 1(2), 137-160.

Frank, M. J. and O' Reilly, R. C., 2006. A Mechanistic Account of Striatal Dopamine Function in Human Cognition: Psychopharmacological Studies with Cabergoline and Haloperidol. Behavioural Neuroscience 120(3), 497-517.

Frank, M. J., Rudy J. W. and O'Reilly R. C., 2003. Transitivity, Flexibility, Conjunctive Representations and the Hippocampus. II. A Computational Analysis. Hippocampus 13, 299-312.

Harsanyi, J. C., and Selten, R., 1988. A General Theory of Equilibrium Selection in Games. Cambridge, MA: MIT Press.

Hershey, J. C., Kunreuther, H. C. and Schoemaker, P.J., 1982. Sources of Bias in Assessment Procedures for Utility Functions. Management Science, 28(8), 936-945.

Hirshleifer, J., 1985. The Expanding Domain of Economics. The American Economic Review 75(6), 53-68.

Green, D. P. and Shapiro, I., 1996. Pathologies of Rational Choice Theory: A Critique of Applications in Political Science. New Haven, CT: Yale University Press.

Kahneman, D. and Tversky, A., 1979. Prospect Theory: Analysis of Decision under Risk. Econometrica, 47(2), 263-292.

Kandori, M., Mailath, G., and Rob, R., 1993. Learning, Mutation and Long Equilibria in Games. Econometrica 61, 27-56.

Khoshnevisan, M, Nahavandi, S., Bhattacharya, S. and Bakhtiary, M., 2008. fMRI studies in neuro-fuzzy and behavioral finance: a case-based approach. Investment Management and Financial Innovations 5(3), 111-121.

Knutson, B., Adams, C. M., Fong, G.W., and Hommer, D., 2001. Anticipation of increasing monetary reward selectively recruits nucleus accumbens. Journal of Neuroscience 21, RC159.

Kreps, D. M., 1990. A Course in Microeconomic Theory. Princeton, NJ: Princeton University Press.

Landa, J. T. and Gheslin, M. T., 1999. The Emerging Discipline of Bioeconomics: Aims and Scope of the Journal of Bioeconomics. Journal of Bioeconomics 1, 5-12.

Levine, D. (2003). Neuroeconomics? Available at: http://www.dklevine.com/papers/neuroeconomics.pdf, last retrieved on 23rd March, 2012.

Loewenstein, G., Rick, S. and Cohen, D., 2008. Neuroeconomics. Annual Review of Psychology 59, 647-72.

Logothetis, N. K., 2008. What we can do and what we cannot do with fMRI. Nature 453(12), 869-878.

Mas-Collel, A., Whinston, M. and Green, J. R., 1995. Microeconomic Theory. New York: Oxford University Press.

Nofsinger, J. R., 2002. The Psychology of Investing. New Jersey: Prentice Hall Series in Finance.

Norman K. A. and O'Reilly R. C., 2003. Modeling Hippocampal and Neocortical Contributions to Recognition Memory: A Complementary Learning Systems Approach. Psychological Review 110(4), 611-46.

O'Reilly, R. C. and Munakata, Y., 2000. Computational explorations in cognitive neuroscience: Understanding the mind by simulating the brain. Cambridge, MA: MIT Press

Paulus, M.P., Rogalsky, C. and Simmons, A., 2003. Increased activation in the right insula during risk-taking decision making is related to harm avoidance and neuroticism. Neuroimage 19, 1439-1448.

Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., and Cohen, J. D., 2003. The neural basis of economic decision-making in the ultimatum game. Science 300*,* 1755-1758.

Schultz, W., 2008. Introduction: Neuroeconomics: the promise and the profit. Philosophical Transactions of the Royal Society *B* 363, 3767-3769.

Simon, H. A., 1979. Rational Decision Making in Business Organizations. The American Economic Review 69(4), 493-513.

Tobler, P. N., Fiorillo, C. D. and Schultz, W., 2005. Adaptive coding of reward value by dopamine neurons. Science 307, 1642-1645.

Volkow, N. D., Wang, G. J., Fowler, J. S., Logan, J., Gatley, S. J., Wong, C., et al., 1999. Reinforcing effects of psychostimulants in humans are associated with increases in brain dopamine and occupancy of D2 receptors. Journal of Pharmacology and Experimental Therapeutics 291, 409-415.

Wager, D., Hernandez, L., Jonides, J. and Lindquist, M., 2007. Elements of functional neuroimaging, in: J.T. Cacioppo, L. G. Tassinary, & Berntson (Eds.), Handbook of Psychophysiology. New York: Cambridge University Press, pp. 19-56.

Wolford, G., Miller, M.B. and Gazzaniga, M., 2000. The left hemisphere's role in hypothesis formation. Journal of Neuroscience 20, 1-4.

Zak, P. J., 2004. Neuroeconomics. Philosophical Transactions of the Royal Society B 359, 1737-1748.

	Run for it	Stand ground
Run for it	(½, ½)	(1, 0)
Stand ground	(0, 1)	(1, 1)

Figure 1: Payoff matrix for a 2x2 coordination game; the payoffs are shown with respect to the row player

Person 2

Person 1